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PREFACE

The National and International Conference on “Shaping the Future of Education,” held on 1 April 2026, brings together educators, researchers, policymakers, and practitioners from diverse backgrounds to explore innovative approaches and emerging trends in education. In an era marked by rapid technological advancement, shifting societal needs, and global interconnectedness, education systems must continuously adapt to prepare learners for the challenges and opportunities of the future.

This conference serves as a platform for the exchange of knowledge, ideas, and best practices that contribute to the transformation of education across local and global contexts. The selected papers included in these proceedings reflect a wide range of perspectives, addressing key themes such as digital learning, educational equity, curriculum innovation, teacher development, and lifelong learning.

We extend our sincere appreciation to all authors for their valuable contributions, as well as to the reviewers and organizing committee for their dedication and commitment to maintaining the academic quality of this conference. Their collective efforts have ensured that these proceedings represent meaningful and impactful scholarly work.

It is our hope that the insights presented in this volume will inspire further research, foster collaboration, and support the ongoing development of education systems that are inclusive, resilient, and forward-looking.

Conference Organizing Committee
1 April 2026

AN AI-ENHANCED ASSESSMENT FOR LEARNING MODEL IN HIGHER EDUCATION: A DESIGN-BASED STUDY OF STUDENT ENGAGEMENT, ANALYTICAL THINKING, AND SELF-REGULATED LEARNING

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Abstract

This study examines the design and implementation of an AI-enhanced Assessment for Learning (AfL) model to support analytical thinking and self-regulated learning in higher education. Adopting a design-based research (DBR) approach, the study emphasizes iterative development, implementation, and refinement within authentic classroom contexts.

The model was implemented as part of regular instruction in a university course during the second semester of the 2025 academic year, involving 120 undergraduate students across four intact groups. The instructional design integrated core AfL practices-such as feedback, self-assessment, and peer interactionwith AI-supported feedback systems and learning analytics.

Data were collected using a mixed-methods approach, including learning outcome measures, student perception surveys, classroom observations, and reflective data. The findings indicate that the model was feasible to implement in real classroom settings and was associated with high levels of student engagement, active use of feedback, and the development of analytical thinking and self-regulated learning processes.

This study contributes to the field by providing a theoretically grounded and practice-oriented model for integrating artificial intelligence into formative assessment. The findings highlight how AI can enhance continuous feedback processes and support adaptive learning in higher education environments.

Keywords: Assessment for Learning; Artificial Intelligence in Education; Design-Based Research; Formative Assessment; Self-Regulated Learning; Analytical Thinking; Learning Analytics; Higher Education

1. Introduction

Assessment for Learning (AfL) has been widely recognized as a key approach to enhancing student learning by integrating assessment into the teaching–learning process (Black & Wiliam, 2009; Wiliam, 2011). Rather than functioning solely as a tool for measuring achievement, AfL emphasizes the use of assessment to support learning through continuous feedback, student involvement, and alignment between learning objectives, instructional activities, and assessment practices. A substantial body of research highlights the critical role of feedback in promoting learning, particularly when it helps students understand their current performance and identify strategies for improvement (Hattie & Timperley, 2007; Carless & Boud, 2018).

In higher education, however, the implementation of AfL remains uneven. Many instructional contexts continue to rely heavily on summative assessment practices, limiting opportunities for students to engage actively with feedback and to develop independent learning capabilities (Carless & Boud, 2018; OECD, 2024). This challenge is particularly significant in the context of contemporary education, where learners are expected to develop higher-order thinking skills and the capacity for self-regulated learning (SRL). SRL involves learners' ability to set goals, monitor progress, and reflect on learning outcomes, and has been identified as a critical factor in academic success (Zimmerman, 2002; Panadero et al., 2018).

Recent developments in artificial intelligence (AI) and learning analytics have created new possibilities for enhancing formative assessment practices. AI technologies can support real-time feedback, adaptive learning pathways, and data-informed instructional decisions, thereby extending the potential of AfL beyond traditional classroom constraints (Zawacki-Richter et al., 2019; Ifenthaler & Yau, 2020; Holmes et al., 2024). Emerging research also suggests that AI-supported feedback systems can improve student engagement and facilitate more effective use of feedback in learning processes (Lim et al., 2024; Khosravi et al., 2024). Nevertheless, the integration of AI into assessment practices remains a complex challenge, as its effectiveness depends not only on technological capabilities but also on its alignment with pedagogical principles (Holmes et al., 2022).

To address these challenges, there is a need for instructional models that meaningfully integrate AfL principles with AI-supported feedback within authentic classroom contexts. Such models should not only enhance feedback processes but also support the development of analytical thinking and self-regulated learning. However, existing studies often focus on isolated technological interventions rather than holistic instructional designs that can be implemented in real educational settings.

In response to this gap, this study adopts a design-based research (DBR) approach to design, implement, and refine an AI-enhanced AfL model in higher education. DBR emphasizes iterative development and evaluation in authentic learning environments, enabling researchers to generate both practical solutions and theoretical insights (Design-Based Research Collective, 2003; Anderson & Shattuck, 2012; McKenney & Reeves, 2019). By situating the study within a real classroom context, this research aims to contribute to a deeper understanding of how AI can be integrated into formative assessment practices to support student engagement, analytical thinking, and self-regulated learning.

Purpose of the Study

The purpose of this study is to design and implement an AI-enhanced Assessment for Learning (AfL) model in authentic higher education contexts, and to examine how such a model can support student engagement, analytical thinking, and self-regulated learning.

Specifically, the study aims to:

1. Design and develop an AI-enhanced AfL model that integrates formative assessment principles with AI-supported feedback and learning analytics.

2. Implement the model within regular classroom instruction to examine its feasibility and alignment with authentic teaching and learning practices.

3. Explore students' learning processes, particularly in relation to engagement, feedback use, analytical thinking, and self-regulated learning.

Consistent with a design-based research (DBR) approach, the study does not seek to test causal relationships, but rather to generate context-sensitive insights and design principles for integrating artificial intelligence into formative assessment in higher education.

Research Questions

- How can an AI-enhanced AfL model be designed and implemented in authentic classroom contexts?
- How do students engage with feedback and learning processes within the model?

2. Literature Review

2.1 Assessment for Learning

Assessment for Learning (AfL) emphasizes the integration of assessment into the teaching–learning process to support student learning (Black & Wiliam, 2009; Wiliam, 2011). Grounded in formative assessment theory, AfL positions assessment not merely as a mechanism for measuring achievement, but as a continuous process for generating and using evidence to guide both teaching and learning. Wiliam (2011) conceptualizes AfL as a set of practices embedded within everyday classroom interactions, including clarifying learning intentions, eliciting evidence of student understanding, providing feedback, and engaging learners in self- and peer-assessment.

Recent scholarship has further conceptualized AfL as a learner-centered and dialogic process. Effective formative assessment involves ongoing interaction between teachers and students, where evidence of learning is actively interpreted and used to adjust instruction (Black & Wiliam, 2009; Black & Wiliam, 2021). In this view, AfL is not a collection of isolated techniques, but a coherent pedagogical approach that integrates assessment, teaching, and learning into a unified process (Carless & Boud, 2018).

A central component of AfL is feedback, which has been widely recognized as one of the most powerful influences on student learning (Hattie & Timperley, 2007). Effective feedback helps learners address three key questions: where they are going, how they are progressing, and what steps are needed next. These processes support learners in identifying gaps between current and desired performance and in developing strategies for improvement. However, recent research suggests that the effectiveness of feedback depends not only on its quality but also on learners' ability to interpret and use it productively (Carless & Boud, 2018).

This perspective has led to the concept of feedback literacy, which refers to learners' capacity to understand, engage with, and act upon feedback. Feedback literacy encompasses cognitive, affective, and behavioral dimensions, including making sense of feedback, managing emotional responses, and applying feedback to improve performance (Carless & Boud, 2018; Molloy et al., 2020). Developing feedback literacy is therefore essential for enabling students to become active participants in the assessment process.

AfL has also been closely linked to the development of self-regulated learning (SRL). Formative assessment practices such as self-assessment and peer assessment encourage learners to take ownership of their learning, engage in goal-setting, monitor their progress, and reflect on outcomes (Panadero et al., 2018; Schunk & Greene, 2018). These processes align with cyclical models of SRL that emphasize planning, monitoring, and reflection (Zimmerman, 2002).

Despite its strong theoretical foundation, the implementation of AfL remains challenging in practice. Many classrooms continue to rely on summative assessment practices, limiting opportunities for meaningful feedback and learner engagement (Carless & Boud, 2018; OECD, 2024). Teachers may also face difficulties in integrating AfL strategies consistently within time-constrained and curriculum-driven environments.

Recent developments in digital technologies, particularly artificial intelligence and learning analytics, have created new opportunities to enhance AfL practices. Technology-enabled environments can support real-time feedback, personalized learning pathways, and continuous monitoring of student progress (Holmes et al., 2022; Viberg et al., 2021). These developments suggest that AfL can evolve into a more adaptive and data-informed process, although careful alignment with pedagogical principles remains essential.

2.2 Self-Regulated Learning and Learner Agency

Self-regulated learning (SRL) refers to learners' active engagement in their own learning processes through goal-setting, strategic action, monitoring, and reflection (Zimmerman, 2002; Pintrich, 2004). Foundational models conceptualize SRL as a cyclical process involving phases of forethought, performance, and self-reflection, in which learners plan, regulate, and evaluate their learning activities. These processes are central to promoting learner autonomy and deeper engagement in learning (Panadero et al., 2018; Schunk & Greene, 2018).

Assessment for Learning (AfL) plays a critical role in supporting SRL by embedding formative assessment practices within everyday instruction. Through mechanisms such as feedback, self-assessment, and peer assessment, AfL enables learners to monitor their progress and adjust their learning strategies continuously (Black & Wiliam, 2009; Wiliam, 2011). Feedback, in particular, has been identified as a key driver of SRL, as it helps learners understand the gap between their current performance and desired learning goals and provides guidance for improvement (Hattie & Timperley, 2007; Carless & Boud, 2018).

Recent research further highlights the close relationship between SRL and learner agency. Learner agency refers to learners' capacity to take ownership of their learning and make intentional decisions about their learning processes. It encompasses autonomy, responsibility, and active engagement, all of which are supported by formative assessment practices (Panadero et al., 2018; Schunk & Greene, 2018). Self- and peer-assessment practices have been shown to enhance learners' ability to evaluate their own work, reflect on progress, and develop metacognitive awareness.

Contemporary studies emphasize the importance of integrating SRL and AfL to promote sustained and meaningful learning. Formative assessment can function as an external scaffold that gradually supports the internalization of self-regulatory processes (Panadero, 2021). Empirical evidence also suggests that learners who actively engage in feedback use and structured reflection demonstrate higher levels of motivation, persistence, and academic performance (Lim et al., 2023; Khosravi et al., 2023).

The emergence of digital technologies, particularly artificial intelligence (AI) and learning analytics, has further expanded opportunities to support SRL and learner agency. AI-enhanced feedback systems can provide real-time, personalized information about learner performance, enabling students to monitor their progress and adjust their strategies more effectively (Holmes et al., 2022; Viberg et al., 2021). These technologies also support adaptive learning pathways, allowing learners to exercise greater control over their learning processes.

However, the development of SRL and learner agency depends not only on access to feedback or technological tools, but also on the design of learning environments that intentionally scaffold learners' engagement in goal-setting, monitoring, and reflection. Without such structured support, students may struggle to effectively interpret feedback or regulate their learning processes (Panadero, 2021).

Therefore, integrating AfL principles with structured instructional design and AI-supported learning environments offers a promising approach for promoting SRL and learner agency. Such integration provides a foundation for designing learning environments in which students are actively engaged in their learning and supported in developing competencies essential for lifelong learning.

2.3 Artificial Intelligence and Learning Analytics

Artificial intelligence (AI) has emerged as a transformative force in education, enabling new forms of teaching, learning, and assessment that extend beyond traditional approaches (Chen et al., 2020; Holmes et al., 2022; Holmes et al., 2024). AI technologies-including machine learning, natural language processing, and intelligent tutoring systems-support the automation and personalization of instructional processes, allowing learning experiences to be tailored to individual learner's needs.

In the context of Assessment for Learning (AfL), AI offers significant potential to enhance formative assessment practices. AI-driven systems can analyze large volumes of learner data in real time, identify patterns of performance, and generate personalized feedback that is timely and actionable (Zawacki-Richter et al., 2019; Holmes et al., 2022). Such capabilities align closely with core AfL principles, particularly the emphasis on continuous feedback to support learning (Hattie & Timperley, 2007). By enabling immediate and iterative feedback cycles, AI can extend the effectiveness of formative assessment beyond traditional classroom constraints.

Learning analytics further complements the role of AI by providing systematic approaches to interpreting educational data and supporting evidence-based decision-making. Learning analytics involves the measurement, collection, analysis, and reporting of data about learners and their contexts to understand and optimize learning processes (Siemens & Baker, 2012). Empirical studies have shown that learning analytics can support adaptive instruction, early identification of learning difficulties, and the development of personalized learning pathways (Gašević et al., 2015; Viberg et al., 2021).

Recent research highlights the combined potential of AI and learning analytics in enhancing formative assessment and learning processes. AI-enhanced feedback systems have been shown to promote student engagement, support active use of feedback, and facilitate the development of self-regulated learning (Lim et al., 2023; Khosravi et al., 2023). These systems enable learners to receive immediate, individualized feedback, which supports key processes such as goal-setting, monitoring, and reflection (Panadero et al., 2018).

In addition, AI-supported learning environments can facilitate higher-order thinking by providing scaffolding, prompts, and adaptive challenges that encourage analytical reasoning and problem-solving (Holmes et al., 2022). When integrated with AfL practices, these technologies can create continuous feedback loops in which learners actively engage with assessment information to improve their understanding and performance.

Despite these opportunities, the integration of AI into educational assessment raises important challenges. Ethical concerns related to data privacy, transparency, and algorithmic bias remain critical (Ferguson, 2019). Moreover, the effectiveness of AI depends not only on technological capabilities but also on its alignment with pedagogical principles. Without such alignment, AI tools may fail to support meaningful learning processes.

Therefore, there is a growing need for instructional models that integrate AI and learning analytics within a coherent pedagogical framework, particularly in relation to AfL. Such models should position technology as a tool to enhance formative assessment practices, while supporting learner engagement, feedback use, and self-regulated learning in authentic educational contexts.

2.4 Toward AI-Enhanced AfL (Expanded Version)

The integration of artificial intelligence (AI) into Assessment for Learning (AfL) represents a significant shift toward more continuous, data-informed, and adaptive assessment processes. While traditional formative assessment practices often rely on periodic feedback, AI-enhanced systems enable the real-time collection and analysis of learning data, allowing for more timely, personalized, and actionable feedback (Tsai et al., 2022; Viberg et al., 2021). This shift expands the potential of AfL by supporting continuous feedback loops that are central to effective learning.

AI technologies-particularly those associated with learning analytics and intelligent feedback systems-can enhance AfL by enabling real-time feedback, adaptive learning pathways, and predictive insights into student performance (Holmes et al., 2022; Ifenthaler & Yau, 2020). These capabilities align closely with the core principles of AfL, especially the use of assessment evidence to inform teaching and support student learning (Wiliam, 2011). By identifying patterns in learner performance and detecting misconceptions, AI-driven systems can provide targeted feedback that supports learners in understanding and improving their performance.

Importantly, the integration of AI within AfL also creates new opportunities to support self-regulated learning (SRL). AI-enhanced feedback environments can facilitate learners' ability to set goals, monitor their progress, and reflect on their learning processes, which are key components of SRL (Panadero et al., 2018). Empirical studies suggest that such environments can enhance student engagement, promote active use of feedback, and support adaptive learning behaviors (Lim et al., 2023; Khosravi et al., 2023). In addition, learning analytics dashboards can provide visual representations of learning progress, enabling both learners and instructors to make more informed decisions and strengthening learner agency (Gašević et al., 2015; Viberg et al., 2021).

Despite these opportunities, the integration of AI into AfL presents several challenges. Ethical concerns related to data privacy, algorithmic bias, and transparency remain critical in AI-supported educational environments (Ferguson, 2019; Holmes et al., 2022). Furthermore, effective implementation requires not only technological infrastructure but also pedagogical capacity, including teachers' data literacy and their ability to design and interpret feedback within AI-supported systems (Ifenthaler & Yau, 2020).

Another key challenge is ensuring that AI enhances rather than replaces pedagogical practices. While AI can automate aspects of feedback and data analysis, meaningful learning depends on human interaction, contextual understanding, and instructional judgment. Therefore, the effectiveness of AI-enhanced AfL depends on its alignment with pedagogical principles and learning theories.

In response to these opportunities and challenges, there is a growing need for instructional models that integrate AfL principles, self-regulated learning, and AI technologies within a coherent pedagogical framework. Such models should emphasize the design of learning environments that support continuous feedback, learner engagement, and adaptive learning processes. However, existing research has often focused on isolated technological interventions rather than comprehensive instructional designs implemented in authentic classroom contexts. This gap highlights the need for design-based approaches that can develop and refine AI-enhanced AfL models in real educational settings.

2.5 Design-Based Research in Educational Innovation

Design-based research (DBR) is an approach that focuses on the systematic development and refinement of educational interventions through iterative cycles of design, implementation, analysis, and revision in authentic learning environments (Design-Based Research Collective, 2003; Anderson & Shattuck, 2012). Unlike traditional experimental research, which often prioritizes control and generalizability, DBR emphasizes the co-evolution of theory and practice, enabling researchers to generate context-sensitive solutions while contributing to theoretical advancement.

A defining characteristic of DBR is its emphasis on iteration and responsiveness to context. Interventions are not treated as fixed treatments but as evolving designs that are continuously refined based on evidence collected during implementation (McKenney & Reeves, 2019). This iterative process allows researchers to address the complexity of real classroom environments, where instructional effectiveness depends on dynamic interactions among learners, teachers, and contextual factors.

DBR is particularly well suited to studies that aim to bridge the gap between educational theory and classroom practice. By situating research within authentic learning environments, DBR enhances ecological validity and ensures that findings are directly relevant to real-world teaching contexts (Anderson & Shattuck, 2012). At the same time, DBR contributes to theory by identifying design principles, underlying learning mechanisms, and the conditions under which instructional innovations are effective (Reeves & McKenney, 2020).

Recent research has highlighted the growing importance of DBR in educational innovation, particularly in contexts involving complex pedagogical and technological integration. DBR has been widely applied in studies of digital learning environments, learning analytics, and artificial intelligence, where interventions must be continuously adapted to evolving technologies and learner needs (Wang & Hannafin, 2005; McKenney & Reeves, 2019). In such contexts, DBR supports the development of scalable and sustainable innovations grounded in both empirical evidence and practical feasibility.

In the context of Assessment for Learning (AfL), DBR provides a valuable framework for embedding formative assessment practices within everyday teaching. AfL requires continuous interaction among teaching, assessment, and learning processes, which aligns closely with the iterative and adaptive nature of DBR. Formative assessment practices are most effective when they are context-sensitive and continuously refined based on learner performance and feedback (Black & Wiliam, 2009; Carless & Boud, 2018).

Furthermore, the integration of artificial intelligence (AI) into AfL presents new opportunities and challenges that are well suited to a DBR approach. AI-enabled systems can support real-time feedback, adaptive learning pathways, and data-driven insights, but their effectiveness depends on how they are integrated into pedagogical practices (Holmes et al., 2022; Zawacki-Richter et al., 2019). DBR enables researchers to examine this integration in practice, exploring how AI tools interact with instructional design, teacher facilitation, and student learning processes.

Therefore, DBR provides a robust methodological framework for developing AI-enhanced AfL models that are both theoretically grounded and practically applicable. By combining iterative design, authentic implementation, and mixed-methods inquiry, DBR enables a comprehensive understanding of how instructional innovations function in real educational settings. This makes it particularly appropriate for studies that seek to design and implement models supporting analytical thinking and self-regulated learning in contemporary classrooms.

3. Methodology

3.1 Research Design

This study adopted a design-based research (DBR) approach to design, implement, and refine an AI-enhanced Assessment for Learning (AfL) model in authentic classroom contexts. DBR is a methodological approach that emphasizes the development of educational innovations through iterative cycles of design, implementation, analysis, and revision in real-world settings (Design-Based Research Collective, 2003; Anderson & Shattuck, 2012; McKenney & Reeves, 2019). It is particularly suitable for addressing complex educational problems while generating both practical solutions and theoretical insights.

The DBR process in this study was structured into three interconnected phases:

(1) Analysis and Exploration Phase

This phase focused on identifying instructional challenges related to the implementation of AfL in classroom practice, particularly the limited use of formative feedback and the lack of integration with digital technologies. Relevant theoretical frameworks, including Assessment for Learning, self-regulated learning, and artificial intelligence in education, were reviewed to inform the initial design of the instructional model.

(2) Design and Development Phase

Based on insights from the analysis phase, an AI-enhanced AfL model was developed by integrating core formative assessment practices-such as goal clarification, evidence elicitation, feedback, and reflection-with AI-supported tools, including real-time feedback systems and learning analytics. The model was designed as a flexible instructional framework adaptable to authentic classroom conditions.

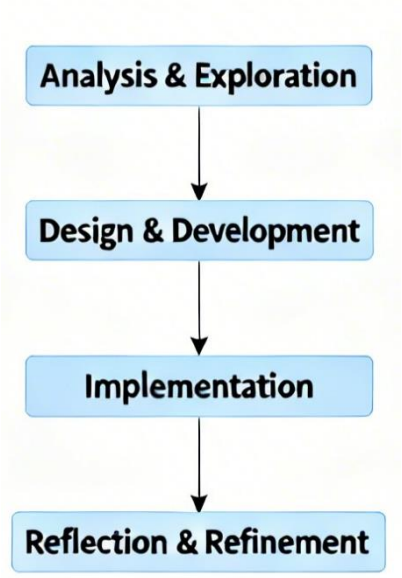
(3) Implementation and Reflection Phase

The model was implemented as part of regular classroom instruction. Data were collected to examine how the model functioned in practice, with a focus on student engagement, feedback use, and learning processes. Insights from implementation were used to iteratively refine the model to ensure alignment with classroom realities.

A key characteristic of DBR is its emphasis on iteration and responsiveness to context, where instructional designs are continuously adapted based on empirical evidence and practitioner feedback (McKenney & Reeves, 2019). In this study, the instructional model was treated as an evolving design rather than a fixed intervention.

Unlike traditional experimental or quasi-experimental designs, which prioritize control and causal inference, DBR focuses on understanding how and why instructional innovations function within complex and dynamic learning environments. This enhances ecological validity, as the model is developed and tested within authentic teaching contexts (Anderson & Shattuck, 2012).

Furthermore, DBR supports the generation of design principles that inform future instructional practice and research. By examining the interaction between pedagogical strategies, technological tools, and learner engagement, this study contributes to understanding how AI-enhanced AfL can be effectively implemented in real classrooms.



The overall DBR process adopted in this study is illustrated in Figure 1.

3.2 Research Context and Participants

The study was conducted as part of regular classroom instruction in the course 0308340: Research and Innovation Development for Learners* during the second semester of the 2025 academic year. The course is offered within the Faculty of Education and focuses on developing students' competencies in research-based learning, innovation design, and reflective practice. This instructional context is particularly suitable for integrating Assessment for Learning (AfL) and self-regulated learning processes.

The participants consisted of 120 undergraduate students across four intact classroom groups. These groups were formed through the university's course registration system and were not reorganized for research purposes. As a result, the study reflects authentic classroom conditions, including natural variation in student abilities, learning styles, and engagement levels.

The use of intact groups is consistent with the principles of design-based research (DBR), which emphasize implementation in real educational settings rather than controlled experimental environments (Anderson & Shattuck, 2012; McKenney & Reeves, 2019). This approach enhances ecological validity, as the instructional model was embedded within existing teaching structures, schedules, and classroom interactions.

All four groups experienced comparable learning conditions in terms of course content, learning objectives, and instructional duration. The same AI-enhanced AfL model was implemented across groups as part of regular teaching activities. The instructor assumed a dual role as both teacher and facilitator, supporting students through learning activities, feedback processes, and reflective practices.

No control or comparison groups were established, as the primary aim of the study was to design, implement, and examine the instructional model in practice rather than to test causal effects. This approach aligns with DBR's focus on understanding how instructional innovations function within complex and dynamic classroom contexts.

Overall, the research context and participant structure support a context-sensitive and practice-oriented investigation, enabling the study to capture realistic patterns of student engagement, feedback use, and self-regulated learning in authentic higher education settings.

3.3 Design and Development of the Instructional Model

The AI-enhanced Assessment for Learning (AfL) model developed in this study was designed through the systematic integration of theoretical frameworks and contextual insights identified during the analysis phase. The model is grounded in three interrelated foundations:

Assessment for Learning (AfL), self-regulated learning (SRL), and artificial intelligence (AI) with learning analytics. These foundations were synthesized to create a pedagogically grounded and context-responsive instructional model suitable for implementation in authentic classroom settings.

3.3.1 Theoretical Foundations of the Model

The design of the instructional model was guided by core principles of AfL, which emphasize the use of assessment to support learning through continuous feedback, active student participation, and alignment between learning objectives, instructional activities, and assessment processes (Black & Wiliam, 2009; Wiliam, 2011). These principles provided the foundation for structuring feedback processes and learning interactions within the model.

To further support learner engagement and autonomy, the model incorporates self-regulated learning (SRL) theory, which highlights learners' capacity to set goals, monitor their progress, and reflect on their learning (Panadero et al., 2018; Schunk & Greene, 2018). The integration of SRL principles ensures that learners are positioned as active agents in the learning process, engaging in continuous self-assessment and learning adjustment.

In addition, the integration of AI and learning analytics enables the model to support data-informed and adaptive feedback processes. AI-supported tools facilitate real-time analysis of learner performance and provide timely, personalized feedback that extends beyond traditional classroom constraints (Holmes et al., 2022; Ifenthaler & Yau, 2020). This technological integration enhances the responsiveness and scalability of formative assessment practices.

The combination of AfL, SRL, and AI forms a coherent framework that supports continuous feedback, learner engagement, and adaptive learning processes. This integrated design provides a foundation for implementing formative assessment practices that are both theoretically grounded and practically applicable in real classroom contexts.

3.3.2 Structure of the AI-Enhanced AfL Model

The developed instructional model consists of five interrelated components that operate within a continuous and iterative learning cycle. These components are designed to align with core principles of Assessment for Learning (AfL) while supporting self-regulated learning (SRL) processes and AI-enhanced feedback mechanisms.

(1) Clarification of Learning Goals

Learning objectives and success criteria are explicitly communicated to students at the beginning of each learning cycle. This process enables learners to understand expectations, align their efforts with intended outcomes, and establish a clear direction for their learning.

(2) Elicitation of Learning Evidence

Students engage in structured learning activities designed to generate evidence of their understanding. These activities may include problem-solving tasks, collaborative discussions, and project-based work, providing opportunities for learners to demonstrate their knowledge and skills.

(3) Feedback (Teacher and AI-Supported)

Feedback is provided through both instructor guidance and AI-supported systems. This dual approach enables timely, personalized, and actionable feedback that supports learners in identifying strengths, addressing misconceptions, and improving their performance.

(4) Reflection and Self-Assessment

Students are encouraged to reflect on their learning processes and evaluate their performance against established criteria. This component supports the development of self-regulated learning by promoting metacognitive awareness and learner responsibility.

(5) Learning Adjustment

Based on feedback and reflection, students revise their work, adjust their learning strategies, and continue the learning process. This iterative adjustment reinforces continuous improvement and supports adaptive learning.

These components function as an integrated and cyclical process rather than a linear sequence. The model emphasizes continuous feedback loops, learner engagement, and iterative refinement, which are consistent with both AfL principles and the design-based research (DBR) approach underpinning this study.

3.3.3 Integration of AI and Learning Analytics

A key innovation of the instructional model lies in the integration of artificial intelligence (AI) and learning analytics to support formative assessment processes. Within the model, AI functions as a mechanism for enhancing feedback and supporting adaptive learning. Specifically, AI-supported tools enable real-time feedback based on student responses, facilitate personalized learning pathways, and generate learning analytics that inform both students and instructors.

This integration enhances the responsiveness and scalability of Assessment for Learning (AfL) practices by enabling continuous feedback loops and data-informed instructional decision-making (Holmes et al., 2022; Zawacki-Richter et al., 2019). Importantly, AI is positioned as a supportive component rather than a replacement for teacher judgment, ensuring that pedagogical decision-making remains central to the instructional process.

3.3.4 Alignment with Design-Based Research Principles

The design and development of the instructional model were guided by core principles of design-based research (DBR), particularly iteration, flexibility, and responsiveness to context (McKenney & Reeves, 2019). The model was conceptualized as an evolving design rather than a fixed intervention, allowing for continuous refinement based on classroom implementation and feedback.

Throughout the development process, emphasis was placed on maintaining alignment between theory and practice, ensuring adaptability to authentic classroom conditions, and integrating pedagogical and technological components into a coherent framework. This approach strengthens both the theoretical grounding and practical applicability of the model, addressing the gap between research-based principles and classroom implementation.

3.3.5 Development of Supporting Instructional Materials

To support the implementation of the instructional model, a set of structured instructional materials was developed. These included lesson plans aligned with AfL principles and AI integration, learning activities designed to promote analytical thinking, assessment tools for capturing learning outcomes and self-regulated learning processes, and reflection prompts to support metacognitive engagement.

These materials were designed to ensure consistency across classroom groups while allowing flexibility for contextual adaptation. This balance between structure and adaptability is consistent with DBR principles and supports the practical implementation of the model in real classroom settings.

In summary, the AI-enhanced AfL model was developed through the integration of AfL principles, self-regulated learning theory, and AI-supported learning analytics within a DBR framework. The model provides a structured yet flexible approach to formative assessment, emphasizing continuous feedback, learner engagement, and iterative learning adjustment. Its design reflects both theoretical rigor and practical applicability, making it suitable for implementation in authentic educational contexts.

3.4 Implementation Process

The implementation of the AI-enhanced Assessment for Learning (AfL) model was conducted as part of regular classroom instruction across four intact student groups during the second semester of the 2025 academic year. The implementation spanned approximately 15 weeks, covering the full duration of the semester in accordance with the university's academic calendar.

Consistent with the principles of design-based research (DBR), the model was implemented in authentic educational settings, allowing it to be enacted, observed, and iteratively refined within real teaching and learning contexts (Anderson & Shattuck, 2012; McKenney & Reeves, 2019).

3.4.1 Overall Implementation Structure

The instructional model was implemented continuously throughout the semester, with each learning cycle structured around five core components: clarification of learning goals, elicitation of learning evidence, feedback (teacher and AI-supported), reflection and self-assessment, and learning adjustment. These components were embedded within weekly instructional sessions, ensuring that formative assessment processes were integrated into ongoing classroom practice rather than treated as discrete activities.

3.4.2 Integration into Regular Teaching Practice

The model was fully integrated into routine teaching practices without a separate intervention phase. Each class session incorporated key AfL principles, including the explicit communication of learning objectives and success criteria, active student participation through problem-solving and collaborative tasks, continuous feedback supported by both instructor and AI tools, and structured opportunities for reflection. This sustained integration allowed the model to function as an ongoing instructional approach rather than a short-term intervention.

3.4.3 Role of AI in the Implementation

Artificial intelligence tools were incorporated to enhance formative assessment processes throughout the semester. These tools supported real-time and iterative feedback, ongoing monitoring of student progress through learning analytics, and adaptive guidance for learning adjustment. The repeated feedback cycles enabled by AI were particularly important for supporting the development of self-regulated learning processes (Holmes et al., 2022).

3.4.4 Iterative Refinement during Implementation

A key feature of the implementation process was its iterative refinement across the semester. The instructional model was continuously adjusted based on classroom observations, student engagement patterns, learner feedback, and instructor reflection. This ongoing refinement reflects the DBR emphasis on responsiveness to context and the continuous improvement of instructional design.

3.4.5 Student Engagement and Learning Processes

Throughout the semester, students engaged in repeated cycles of collaborative learning, feedback interaction, reflection, and learning adjustment. These processes supported sustained engagement and enabled students to gradually develop analytical thinking and self-regulated learning capabilities through continuous feedback and iterative practice.

3.4.6 Instructor Role

The instructor played a central role in facilitating the implementation of the model. Responsibilities included organizing learning activities, providing formative feedback, interpreting AI-generated data, and adapting instructional strategies based on classroom evidence. This dual role as both teacher and facilitator ensured coherence in the implementation and alignment with pedagogical objectives.

In summary, the implementation of the AI-enhanced AfL model was conducted over a full academic semester within authentic classroom settings. The extended duration enabled sustained engagement, iterative refinement, and continuous feedback cycles. This implementation approach reflects the core principles of design-based research, emphasizing contextual responsiveness, ongoing adaptation, and the integration of pedagogical and technological elements.

3.5 Data Collection (Mixed-Methods Approach)

To obtain a comprehensive understanding of the implementation of the AI-enhanced Assessment for Learning (AfL) model, this study employed a mixed-methods approach, integrating both quantitative and qualitative data sources. This approach aligns with the principles of design-based research (DBR), which emphasize the use of multiple forms of evidence to capture the complexity of learning processes in authentic contexts (McKenney & Reeves, 2019).

Data were collected throughout the second semester of the 2025 academic year (approximately 15 weeks), enabling the examination of both ongoing learning processes and overall patterns of student development.

3.5.1 Quantitative Data

Quantitative data were collected to describe patterns of student learning, engagement, and perceptions during the implementation of the instructional model.

Students' analytical thinking was assessed through structured tasks embedded within course activities. These tasks required learners to analyze problems, interpret information, and propose solutions in authentic learning contexts, providing an indication of cognitive engagement and development.

Self-regulated learning (SRL) was measured using a self-report questionnaire adapted from established SRL frameworks (Panadero et al., 2018; Schunk & Greene, 2018). The instrument captured key dimensions of SRL, including goal-setting, monitoring, and reflection.

In addition, students' perceptions of the AI-enhanced AfL model were collected using a structured questionnaire covering dimensions such as clarity of learning goals, usefulness of feedback, engagement in learning activities, and perceived learning benefits. All quantitative instruments employed a 5-point Likert scale, allowing for the analysis of central tendencies and variability.

3.5.2 Qualitative Data

Qualitative data were collected to provide in-depth insights into how the instructional model functioned in practice and how students experienced the learning process.

Classroom observations were conducted throughout the semester to examine student participation, interaction patterns, and the use of feedback (both teacher- and AI-supported). Field notes were recorded systematically to capture key events and emerging patterns.

Student reflective responses were collected as part of the instructional process. These reflections provided insights into students' understanding of learning goals, their use of feedback, and their learning strategies and adjustments. Reflective data were gathered at multiple points during the semester.

Additional qualitative data were obtained through informal student feedback, including classroom discussions and spontaneous comments. These data provided contextual insights into learners' experiences and perceptions of the instructional model.

3.5.3 Data Collection Procedures

Data collection was conducted continuously throughout the semester rather than at a single point in time. This approach enabled the capture of changes in student engagement, patterns of feedback use, and the development of self-regulated learning processes over time. Quantitative data were collected at designated points, while qualitative data were gathered on an ongoing basis to support iterative refinement of the instructional model.

3.5.4 Trustworthiness and Data Integration

To enhance the credibility and rigor of the study, several strategies were employed. These included triangulation across multiple data sources, prolonged engagement within the classroom context over the 15-week period, and the integration of quantitative and qualitative data during analysis to provide a holistic understanding of the instructional process.

The integration of multiple data sources allowed for a more comprehensive interpretation of how the AI-enhanced AfL model supported learning processes in practice.

Overall, the data collection process was designed to capture both measurable learning outcomes and rich contextual insights into student learning. By employing a mixed-methods approach within a DBR framework, the study provides a nuanced understanding of how the instructional model functions in authentic classroom settings.

3.6 Data Analysis

Data analysis in this study was conducted using a mixed-methods approach, integrating quantitative and qualitative data to provide a comprehensive understanding of how the AI-enhanced Assessment for Learning (AfL) model functioned in authentic classroom contexts. This approach aligns with design-based research (DBR), which emphasizes the use of multiple data sources to capture the complexity of learning processes and instructional implementation (McKenney & Reeves, 2019).

3.6.1 Quantitative Data Analysis

Quantitative data were analyzed using descriptive statistics, including mean (M) and standard deviation (SD), to examine patterns in student learning, engagement, and perceptions. The analysis focused on three key areas.

First, analytical thinking was examined through scores derived from structured learning tasks, providing an indication of students' cognitive engagement and development across the implementation period. Second, self-regulated learning (SRL) was analyzed using responses from the SRL scale to assess students' use of goal-setting, monitoring, and reflection strategies. Third, student perception data were analyzed to describe learners' views on learning activities, feedback processes, and overall learning experiences.

Descriptive statistics were interpreted using established criteria for Likert-scale data to categorize levels of perception (e.g., low, moderate, high). The purpose of this analysis was not to test hypotheses or establish causal relationships, but to identify trends and patterns associated with the implementation of the instructional model.

3.6.2 Qualitative Data Analysis

Qualitative data were analyzed using thematic analysis following the procedures outlined by Braun and Clarke (2006). The analysis involved familiarization with the data, initial coding of meaningful segments, identification and refinement of themes, and interpretation of patterns.

The analysis focused on themes related to student engagement in learning activities, the use and interpretation of feedback (both teacher- and AI-supported), the development of self-regulated learning processes, and patterns of classroom interaction. Data from classroom observations, student reflections, and informal feedback were systematically coded and organized to support interpretation.

3.6.3 Integration of Quantitative and Qualitative Data

Quantitative and qualitative data were integrated through triangulation to provide a more comprehensive understanding of the instructional model. Quantitative findings were used to identify general trends, while qualitative data provided contextual explanations for these patterns.

For example, patterns observed in SRL scores were interpreted alongside students' reflective accounts of learning strategies, and perception data were examined in relation to observed classroom engagement. Similarly, students' use of feedback was analyzed using both survey responses and qualitative evidence. This integrative approach enhances the depth and validity of the findings by combining numerical patterns with rich contextual insights.

3.6.4 Rigor and Trustworthiness

Several strategies were employed to enhance the rigor and trustworthiness of the analysis. These included triangulation across multiple data sources, iterative analysis conducted throughout the implementation process, and transparent analytical procedures for both quantitative and qualitative data. In addition, all analyses were aligned with the study's objectives, focusing on understanding the implementation of the model and associated learning processes.

In summary, the analysis combined descriptive statistical methods and thematic qualitative analysis within a mixed-methods framework. The integration of multiple data sources enabled a comprehensive examination of how the AI-enhanced AfL model supported student learning, engagement, and self-regulated learning processes in authentic classroom contexts.

4. Results

This section presents the findings from the implementation of the AI-enhanced Assessment for Learning (AfL) model in authentic classroom contexts over a full academic semester. The results are derived from the integration of quantitative and qualitative data, providing a comprehensive understanding of student learning processes, engagement, and feedback use.

4.1 Overview of Implementation Outcomes

Overall, the findings indicate that the instructional model was feasible to implement within regular classroom settings. Across the 15-week implementation period, the model was successfully integrated into routine teaching practices without disrupting instructional flow, supporting the ecological validity emphasized in design-based research (Anderson & Shattuck, 2012).

Quantitative results suggest that students demonstrated consistently high levels of engagement, positive perceptions of feedback processes, and active participation in learning activities (see Table 1 and Table 2). These patterns were further supported by qualitative evidence, which indicated that students actively engaged with feedback, participated in collaborative learning tasks, and demonstrated iterative learning behaviors throughout the course.

In particular, students showed evidence of sustained engagement in feedback processes, including interpreting feedback, revising their work, and applying feedback to subsequent learning tasks. These findings are consistent with prior research highlighting the importance of feedback in supporting learning and engagement (Carless & Boud, 2018; Hattie & Timperley, 2007).

Qualitative data also revealed that the model supported continuous learning cycles characterized by task engagement, feedback interaction, reflection, and learning adjustment. These iterative processes suggest that the model functioned as intended, facilitating ongoing learning rather than isolated instructional activities.

Taken together, the findings indicate that the AI-enhanced AfL model was not only feasible to implement but also supported active learning processes, continuous feedback use, and sustained student engagement in authentic classroom contexts.

4.2 Quantitative Results

4.2.1 Analytical Thinking

The analysis of students' analytical thinking, based on structured learning tasks embedded within course activities, indicated a progressive development over the implementation period. Students demonstrated increasing ability to analyze problems, interpret information, and propose solutions within authentic learning contexts.

Descriptive patterns suggest that students engaged actively with analytical tasks, particularly during collaborative and problem-based learning activities. These findings indicate that the instructional model supported the development of higher-order thinking processes, consistent with the integration of feedback, reflection, and iterative learning cycles.

4.2.2 Self-Regulated Learning (SRL)

Results from the self-regulated learning (SRL) scale indicated that students reported consistently high levels of engagement in key SRL processes, including goal-setting, monitoring, and reflection. As shown in Table 2, mean scores ranged from 4.35 to 4.50, indicating a high level of self-regulated learning.

Reflection demonstrated the highest mean score ($M = 4.50$, $SD = 0.49$), suggesting that students actively engaged in evaluating their learning and making adjustments based on feedback. Goal-setting ($M = 4.40$, $SD = 0.55$) and monitoring ($M = 4.35$, $SD = 0.57$) were also reported at high levels, indicating that students were able to regulate their learning processes throughout the implementation.

4.2.3 Student Perceptions of the Instructional Model

Students' perceptions of the AI-enhanced AfL model were generally positive across all measured dimensions. As presented in Table 1, mean scores ranged from 4.45 to 4.55, reflecting high levels of agreement regarding the effectiveness of the instructional model.

Specifically, students reported high levels of perceived learning benefits (M = 4.55, SD = 0.46) and usefulness of feedback (M = 4.52, SD = 0.48), indicating that feedback processes-both teacher- and AI-supported-played a significant role in supporting learning. Perceptions of learning goal clarity (M = 4.45, SD = 0.52) and engagement in learning activities (M = 4.47, SD = 0.50) were also rated highly.

These findings suggest that students perceived the instructional model as supportive of their learning processes, particularly in relation to feedback use, engagement, and understanding of learning expectations.

Table 1. Student Perceptions of the Instructional Model

Dimension	**M**	**SD**	**Interpretation**
Learning goals	4.45	0.52	High
Feedback	4.52	0.48	High
Engagement	4.47	0.50	High
Learning benefits	4.55	0.46	High

As shown in Table 1, students reported high levels of perception across all dimensions (M = 4.45–4.55), indicating positive engagement with the instructional model.

The results presented in Table 1 indicate consistently high levels of student perceptions across all dimensions of the instructional model. The highest mean score was observed for perceived learning benefits (M = 4.55, SD = 0.46), suggesting that students recognized the value of the instructional approach in supporting their learning. Similarly, the usefulness of feedback (M = 4.52, SD = 0.48) was rated highly, reflecting the effectiveness of both teacher- and AI-supported feedback in guiding student learning.

Although slightly lower, scores for clarity of learning goals (M = 4.45, SD = 0.52) and engagement in learning activities (M = 4.47, SD = 0.50) remained within the high range, indicating that students were able to understand expectations and actively participate in the learning process. The relatively low standard deviation values across all dimensions suggest consistency in student responses, reinforcing the reliability of the findings.

Table 2 shows that students demonstrated high levels of self-regulated learning, particularly in reflection (M = 4.50, SD = 0.49).

Table 2. Self-Regulated Learning (SRL)

Component	**M**	**SD**
Goal setting	4.40	0.55
Monitoring	4.35	0.57
Reflection	4.50	0.49

As shown in Table 2, students demonstrated high levels of self-regulated learning across all components. Reflection yielded the highest mean score (M = 4.50, SD = 0.49), indicating that students actively engaged in evaluating their learning and adjusting based on feedback. This finding suggests that reflective processes were strongly supported within the instructional model.

Goal setting (M = 4.40, SD = 0.55) and monitoring (M = 4.35, SD = 0.57) were also reported at high levels, indicating that students were able to plan and track their learning progress effectively. The slightly higher variability in these components may reflect differences in students' prior experience with self-regulated learning strategies.

Overall, the results suggest that the instructional model supported multiple dimensions of self-regulated learning, particularly in fostering reflective practices and ongoing learning adjustment.

4.3 Qualitative Results

4.3.1 Student Engagement and Participation

Qualitative data from classroom observations and student reflections indicated consistently high levels of engagement throughout the implementation. Students actively participated in collaborative learning activities, problem-solving tasks, and peer discussions, demonstrating sustained involvement in learning processes.

The structured design of learning activities, combined with continuous feedback, appeared to support active participation over time. Observational data further suggested that students became increasingly engaged as they progressed through iterative learning cycles, indicating that the instructional model facilitated sustained and meaningful engagement in classroom activities.

4.3.2 Use of Feedback

Qualitative findings indicate that students actively engaged with feedback provided by both the instructor and AI-supported systems. Students described feedback as helpful in identifying their strengths and areas for improvement, and reported using feedback to revise their work across multiple learning cycles.

In particular, AI-generated feedback was perceived as timely and responsive, providing immediate input that complemented instructor guidance. This combination of human and AI-supported feedback enabled students to engage in continuous improvement processes. These findings suggest that feedback was not only received but actively used as part of the learning process, reflecting key principles of Assessment for Learning.

4.3.3 Development of Self-Regulated Learning

Student reflections revealed increased awareness of learning processes, particularly in relation to goal-setting, monitoring, and strategy adjustment. Students reported engaging in reflection and self-assessment as part of their learning routines, indicating the development of self-regulated learning practices.

Qualitative evidence suggests that students gradually became more capable of evaluating their own performance and making informed adjustments to their learning strategies. This progression reflects the role of iterative feedback and structured reflection in supporting the development of self-regulated learning over time.

Overall, qualitative findings indicate that the instructional model supported active student engagement, meaningful use of feedback, and the development of self-regulated learning processes. These findings complement the quantitative results by providing contextual insights into how students experienced the learning process and how the model functioned in practice.

4.4 Integration of Quantitative and Qualitative Findings

The integration of quantitative and qualitative findings provides a comprehensive understanding of the implementation of the AI-enhanced Assessment for Learning (AfL) model. Quantitative results identified general patterns of student engagement, learning development, and positive perceptions, while qualitative data offered contextual explanations that illuminate how these patterns emerged in practice.

For instance, the high levels of self-regulated learning (SRL) observed in quantitative measures were supported by qualitative evidence from student reflections, which demonstrated active engagement in goal-setting, monitoring, and learning adjustment. Similarly, positive perception scores were consistent with observational data indicating active participation, sustained engagement, and meaningful interaction with feedback during classroom activities.

This triangulation of data strengthens the interpretation of the findings by linking measurable outcomes with lived learning experiences. It also highlights the role of the instructional model in supporting iterative learning processes, where feedback, reflection, and adjustment are continuously enacted in authentic classroom contexts.

4.5 Summary of Findings

Overall, the findings indicate that the AI-enhanced AfL model was successfully implemented within authentic classroom settings and integrated effectively into regular teaching practices. The results demonstrate that students engaged actively in learning activities and feedback processes, supported by both teacher guidance and AI-enhanced feedback systems.

The findings further suggest that the instructional model supported the development of analytical thinking and self-regulated learning, as evidenced by both quantitative patterns and qualitative insights. In particular, the integration of AI-supported feedback contributed to more timely and continuous feedback cycles, enabling students to engage in ongoing learning adjustment.

Taken together, these findings highlight the practical applicability of the instructional model and its alignment with design-based research principles, particularly in terms of iterative refinement, contextual responsiveness, and the integration of pedagogical and technological components. The results provide evidence that the model can support meaningful learning processes in real classroom contexts.

5. Discussion

This study examined the design and implementation of an AI-enhanced Assessment for Learning (AfL) model in authentic classroom contexts. The findings provide evidence that the model supported student engagement, feedback use, and the development of self-regulated learning processes. This section interprets these findings in relation to existing theoretical frameworks and recent research.

5.1 Assessment for Learning as a Feedback-Centered Process

The findings reinforce the central role of feedback in Assessment for Learning (AfL), as proposed by Black and Wiliam (2009) and Wiliam (2011). Students were not only exposed to feedback but actively engaged in interpreting and applying it across iterative learning cycles. This supports the conceptualization of feedback as a process that enables learning, rather than merely an evaluative mechanism (Carless & Boud, 2018).

The integration of continuous feedback within the instructional model appears to have facilitated ongoing learning adjustment, aligning with feedback literacy frameworks that emphasize learners' capacity to understand and use feedback effectively (Boud et al., 2024). These findings suggest that structured feedback processes are critical for transforming assessment into a tool for learning.

5.2 Development of Self-Regulated Learning

The results indicate that the instructional model supported the development of self-regulated learning (SRL), particularly in terms of goal-setting, monitoring, and reflection. These processes are consistent with established SRL models, which emphasize cyclical learning processes involving planning, performance, and self-reflection (Zimmerman, 2002; Panadero et al., 2018).

The integration of reflection and self-assessment within the AfL framework appears to have created conditions that encouraged students to take an active role in regulating their learning. This supports previous research indicating that formative assessment practices can foster metacognitive awareness and learner autonomy (Schunk & Greene, 2018; Broadbent & Poon, 2024).

Importantly, the findings suggest that SRL development is not an isolated outcome but emerges from sustained engagement in feedback-rich learning environments. The iterative structure of the model, combined with continuous feedback, appears to have supported the gradual internalization of self-regulatory processes.

5.3 Role of AI in Enhancing Formative Assessment

A key contribution of this study lies in demonstrating how artificial intelligence (AI) can be meaningfully integrated into formative assessment practices. The findings indicate that AI-supported feedback enhanced the timeliness and continuity of feedback processes, complementing instructor guidance rather than replacing it.

This aligns with recent research highlighting the potential of AI to support real-time feedback, learning analytics, and adaptive learning pathways (Holmes et al., 2024; Lim et al., 2024; Viberg et al., 2024). However, the findings also emphasize that the effectiveness of AI depends on its pedagogical integration. AI functioned most effectively when embedded within AfL principles, where feedback was structured, purposeful, and aligned with learning goals.

These results suggest that AI should be conceptualized as a mediating tool within pedagogical systems, rather than as an independent instructional solution. The combination of AI and AfL appears to be critical for creating meaningful and sustainable learning experiences.

5.4 Contribution of the Design-Based Research Approach

The use of a design-based research (DBR) approach was instrumental in enabling the development and refinement of the instructional model within authentic classroom contexts. By focusing on iterative implementation and contextual responsiveness, DBR allowed the study to capture the dynamic interactions between learners, instructors, and technological tools (Anderson & Shattuck, 2012; McKenney & Reeves, 2019).

Rather than testing causal relationships, the study provides insight into how instructional innovations function in practice. This contributes to the development of design principles for integrating AI into AfL, particularly in relation to feedback processes, learner engagement, and self-regulated learning. These findings support the value of DBR in bridging the gap between educational theory and classroom practice.

5.5 Implications for Teaching and Learning

The findings of this study have several implications for educational practice. First, they demonstrate that AfL can be effectively embedded within regular classroom instruction when supported by structured processes and appropriate technological tools. This suggests a pathway for addressing challenges in implementing formative assessment in everyday teaching.

Second, the integration of AI into AfL provides opportunities to enhance feedback processes, particularly in terms of timeliness, personalization, and continuity. However, the findings underscore the importance of maintaining teacher agency, as pedagogical judgment remains central to effective instruction.

Third, the study highlights the importance of designing learning environments that promote active engagement, reflection, and feedback use. These elements are essential for supporting the development of analytical thinking and self-regulated learning in contemporary educational contexts.

5.6 Limitations and Future Research

Despite its contributions, this study has several limitations. First, it was conducted within a single course and institutional context, which may limit the transferability of the findings. Second, the study focused on implementation and learning processes rather than causal effects, and therefore does not provide evidence of impact in experimental terms.

Third, the integration of AI was context-specific, and different tools or systems may yield different outcomes. Future research could extend this work by examining the model in diverse educational contexts, exploring the long-term development of self-regulated learning, and investigating the scalability of AI-enhanced AfL models.

6. Conclusion

This study aimed to design and implement an AI-enhanced Assessment for Learning (AfL) model within authentic classroom contexts using a design-based research (DBR) approach. The findings indicate that the model can be effectively integrated into regular instructional practice and supports key learning processes, particularly student engagement, feedback use, and self-regulated learning.

The developed model provides a structured yet flexible framework that integrates core AfL principles-goal clarification, evidence elicitation, feedback, and reflection-with AI-supported feedback and learning analytics. This integration enables continuous and iterative learning cycles, fostering active learner participation in monitoring and improving their own learning.

A key contribution of this study lies in demonstrating how AI can be meaningfully integrated into formative assessment through pedagogically grounded design. Rather than positioning AI as a standalone solution, the study highlights its role as a mediating tool that enhances feedback processes when aligned with established learning theories. This contributes to the growing body of research on AI-enhanced formative assessment by offering a context-sensitive and practically applicable instructional model.

From a methodological perspective, the use of a DBR approach enabled the iterative development and refinement of the model within real classroom environments. This provides valuable insights into how instructional innovations can be designed and implemented in ways that are both theoretically informed and practically feasible.

The findings have important implications for teaching and learning, suggesting that the integration of AI into AfL can enhance the timeliness, continuity, and responsiveness of feedback processes. Such integration supports the development of learner-centered environments that promote analytical thinking and self-regulated learning.

However, the study is limited to a specific course and institutional context, and the findings should be interpreted accordingly. Future research could extend this work by examining the model in diverse educational settings, exploring long-term learning outcomes, and investigating the scalability of AI-enhanced AfL practices.

In conclusion, this study provides both theoretical and practical contributions to the integration of AI in formative assessment. The findings suggest that AI-enhanced AfL represents a promising direction for supporting meaningful learning processes in contemporary educational contexts.

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